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BENEFITS OF CUSTOMER PROFITABILITY ANALYSIS REPORTS IN REPEATED BUDGET ALLOCATION DECISION MAKING

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ABSTRACT

We study how decision makers learn to improve performance across repeated budget allocation decisions. The costing system they use should be able to provide information that is of incremental value over mere outcome feedback. We report an experiment demonstrating that customer profitability analysis (CPA) using activity based costing facilitates learning of the most appropriate allocation of a marketing budget among customers.

In a difficult learning environment, participants receiving CPA information made closer-to-optimal budget allocation decisions, resulting in higher cumulative profits compared to subjects receiving traditional accounting reports. In easier learning environments, CPA yielded a smaller additional benefit over a traditional costing system combined with outcome feedback.

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1. Introduction

Today a large number of companies claim to be customer-driven (Foster, Gupta and Sjoblom, 1996). Many costs are indeed not only incurred in production but also in marketing, distribution, administration, research and development (Selnes, 1992). Foster and Gupta (1994) illustrate that in major industries selling, general and administrative expenses range from 34 till 53% of total sales. Many companies serve varied customers with heterogeneous demands and costs (Shapiro, Rangan, Moriarty and Ross, 1987). A market orientation, defined as the organisation's ability to respond to current and future customer needs (Kohli and Jaworski, 1990), is considered a distinctive competency that yields a competitive advantage. Goebel, Marshall and Locander (1998) state that market- and customer-oriented activities represent a major investment for a firm and insight in ways various customers consume these resources is the necessary key in implementing a market orientation.

Despite the increased customer orientation and increasing customer costs many companies still use traditional accounting systems to allocate customer costs to products or customers. Most management accounting systems focus on products, departments or regions. Rarely can a management accounting system produce customer profitability figures (Anandarajan and Christopher, 1987; Foster, Gupta and Sjoblom, 1996; Innes and Mitchel, 1995; Swenson, 1995) and thereby contribute to understanding of the cost of reaching and serving particular types of buyers (Johnson and Kaplan, 1991). In a traditional accounting system, marketing costs are allocated among customers using sales (volume) as a driver. It assumes that each dollar of revenue contributes equally to net income. When customers are heterogeneous, revenues as well as service and marketing costs may vary substantially across customers (Foster, Gupta and Sjoblom, 1996; Ward, 1992), causing differences in customer profitability. Revenues may differ due to different prices or different selling volumes across customers. Differences in costs arise from various ways in which customers use a company's resources. Customers may differ markedly in the marketing support they need. It is more costly to serve customers ordering very small quantities compared to customers ordering large quantities of the same product. Therefore, the resulting contribution margin in a traditional accounting system is a poor indication of profitability and often results in managers making the wrong decisions with severe consequences (Selnes, 1992).

Several authors criticise traditional accounting systems and propose activity based costing (ABC) as an alternative, claiming that it results in more appropriate cost figures (Foster, Gupta and Sjoblom, 1996; Goebel, Marshall and Locander, 1998; Kaplan and Cooper, 1997; Selnes, 1992). Because sales dollars as an allocation base may or may not correlate highly with after-the-sale expenditures, they contend it is more logical and accurate to use actual service activities, such as number of deliveries, to allocate these expenses. There are different ways in which different customers demand a company's resources. Customer profitability analysis (CPA), using ABC, identifies the activities stemming from servicing a particular customer. The costs of these activities are allocated to the customer that caused them, resulting in more accurate profit information (Petty and Goodman, 1996). The superior information provided by CPA should allow managers to learn more from the feedback they receive from the market, and achieve a better fit between their budget allocations and the needs of the market.

Research on the use of CPA to enhance decision-making is very limited. Goebel, Marshall and Locander (1998) claim that despite the apparent usefulness of ABC information in enhancing marketing performance, no definitive studies exists that specifically address the impact of ABC information on marketing decision making. Foster and Gupta (1994) claim that an unresolved issue today is the effect on management decisions of reporting different levels of customer-related information. Indeed, much of the evidence is anecdotal or based on case studies (Anandarajan and Christopher, 1987; Foster, Gupta and Sjoblom, 1996; Kaplan and Cooper, 1997; Selnes, 1992; Ward, 1992). The major contribution of our research is that it tries to fill this gap by investigating systematically whether and when accounting feedback in the form of CPA-information (using ABC) will improve the profitability of marketing budget allocation decisions.

2. Heuristics in functional learning and the role of accounting feedback

Decision makers do not know all parameters of the economic environment in which they operate (Day and Grooves, 1975) and are therefore unable to calculate the optimal allocation which results in maximum profitability. Even if managers would be completely informed, optimal allocation rules would be difficult to calculate

(Busemeyer, Swenson and Lazarte, 1986). In the absence of such information, allocation decisions are made on the basis of hunches, traditions or easily justifiable heuristics. It seems reasonable however to expect that these allocation rules will improve after experience with outcome feedback.

Dickhaut and Lere (1983) argue that decision makers in a repeated forecasting task with profit feedback use simple iterative heuristic procedures to approach the optimal solution. Stevenson, Busemeyer and Naylor (1990) label this the "hill climbing" heuristic. Metaphorically it can be compared with a hiker finding his way to the top of a hill in the dark. If a step leads uphill, then he will continue in the same direction, if a step leads downhill, then he changes directions. Stevenson, Busemeyer and Naylor (1990) state that this heuristic can be applied to resource allocation problems as well. If a previous change in allocation policy produces an increase in the objective function value, then the next change will be in the same direction as the previously successful change. For example, let us assume that the decision maker increases profits by increasing the budget allocated to customer A, and decreasing the budget to customer B. Following the heuristic, the next trial he will continue to increase the budget to A and to decrease the budget to B. However, if the previous change produces a decrease in the objective function value, then the decision maker will try to improve by changing directions (e.g. by reducing A's budget and/or increasing B's budget). Experimental results support the use of hill climbing heuristics in repeated resource allocation tasks when subjects were given feedback about the outcome of their allocation policies (Busemeyer and Myung, 1987; Busemeyer, Swenson and Lazarte, 1986).

Researchers in accounting are primarily interested in the effect of accounting information on the application of this heuristic, and the resulting quality of allocation decisions. But the evidence on the use of this learning principle in accounting is scarce. Turner and Hilton (1989) showed in an iterative forecasting task that subjects adjusted next-period production quantity forecasts according to a hill climbing heuristic (see also Dickhaut and Lere, 1983). Subjects received profits, computed under variable costing or absorption costing, as feedback. If an increase in production quantity resulted in an increase in profits computed under either accounting system, the majority of the participants increased their production quantity the next trial as predicted by the heuristic.

Gupta and King (1997) reported the results of an experiment with a repeated forecasting task. They found that subjects adjusted their product cost forecasts according to an iterative procedure, after receiving profit feedback on their decisions. If an increase in product cost forecast resulted in an increase in profits, most subjects continued to increase the forecast on the next trial. Half of the participants were given a head start by providing more elaborated accounting information. At the beginning of the experiment this cost system using several cost drivers displayed a product cost forecast closer to optimal profit. Subjects anchored on this point and started making adjustments following the iterative procedure. Subjects with baseline (and less accurate) cost information using only one driver, started from a point further away from optimal profit and therefore performed worse. The authors found no evidence that a more elaborated (and more accurate) accounting system would have more value in a complex environment compared to a simple environment. This may be due to the fact that both economic environments consisted of linear demand and cost structures and that their subjects received accounting info only once. We introduce non-linearity in our setting and accounting information is provided after every trial.

3. Hypotheses

Gupta & King (1997) found that a more accurate accounting system using several drivers is superior to a baseline accounting system. Their setting consisted of three different products, which consumed different amounts of resources in the production process. In today's business environment customers are also often heterogeneous (Foster, Gupta and Sjoblom, 1996; Shapiro, Rangan, Moriarty and Ross, 1987) and the demands different customers place on a company's resources may vary substantially. Many authors claim that allocating marketing expenses using activity drivers (ABC) results in more appropriate customer profitability figures, reflecting the differences between customers, compared to a traditional accounting system (Goebel, Marshall and Locander, 1998; Kaplan and Cooper, 1997; Petty and Goodman, 1996; Selnes, 1992).

In our experiment, participants assume the role of marketing managers, faced with the task of allocating a sales budget among three different customers in order to increase firm profitability. Besides feedback on total profits, they receive after every trial accounting information that displays profits for each customer. CPA information using ABC closely approximates real economic profit differences between customers. In a CPA report the influence of the sales budget on profitability per customer is better reflected. If an increase in the sales budget allocated to one customer increases profits, the CPA system will in most cases also display a profit increase for that customer. This reliable profit feedback facilitates hill climbing (Busemeyer, Lazarte and Swenson, 1986; Dickhaut and Lere, 1983) at the individual customer level. Consequently subjects choose more appropriate adjustments in the subsequent period.

Traditional accounting information, using sales as a cost driver, deviates markedly from underlying economic reality. The consequences of a sales budget allocation on the profitability per customer is less obvious and therefore less reliable for applying hill climbing on customer level. We expect that subjects, receiving CPA information, outperform participants receiving traditional accounting information:

H1: People receiving CPA information will realise higher profits compared to subjects receiving traditional accounting systems in both economic environments.

$$\pi \text{ (CPA)} > \pi \text{ (TRAD)}$$

Our experiment introduces two economic environments (Mantrala, Prabhakant and Zoltners, 1992) which differ in the degree of complexity (Gupta and King, 1997). We expect that the difference in performance between a CPA report and a traditional system in a simple environment is smaller. In a simple learning environment, subjects may learn a great deal from total profit feedback. The superior information which CPA using activity drives provides, may be secondary in improving firm profitability.

In a complex environment it is more difficult to learn from total profit feedback and reliable additional information on customer profitability may be required. Busemeyer, Lazarte and Swenson (1986) mention that additional information over pure outcome feedback may facilitate learning. Both accounting systems provide additional information but CPA approximates customer heterogeneity thereby providing reliable information at customer level. Therefore we predict that CPA will continue to allow reliable hill climbing in complex environments, where the traditional system may fail:

H2: The value of a CPA report is greater in a complex economic environment compared to a simple economic environment.

$$\frac{\pi\,(\text{Complex\_CPA}) - \pi\,(\text{Complex\_TRAD})}{\pi\,(\text{Complex\_TRAD})} > \frac{\pi\,(\text{Simple\_CPA}) - \pi\,(\text{Simple\_TRAD})}{\pi\,(\text{Simple\_TRAD})}$$

4. Experiment

4.1. Experimental design

In our experimental design two factors were manipulated. The first factor is the **economic environment**. About half of our participants were assigned to a complex economic environment while the other half worked in a more simple economic environment. The difference in complexity is due to the different shapes of the response functions. This allowed us to evaluate the information value of a CPA report in learning environments differing in the degree of complexity.

The other factor is the **costing system**. About half of our subjects received a traditional accounting report (traditional information) using sales volume as cost driver. This report deviates noticeably from the underlying economic profitability structure, because sales volume is a bad driver to allocate customer costs. The other half of our participants received a CPA-report (customer profitability information), using activities as cost drivers. We designed this CPA costing system in a way that it corresponds close to economic profit reality.

Economic environment

Mantrala, Prabhakant and Zoltners (1992) present two economic environments, characterised by *Concave* and *S-shaped* sales response functions which are often used in marketing research (Arndt and Simon, 1980; Little, 1970; Lodish, 1971; McIntyre and Ryans, 1983). These two alternative marketing environments are the building blocks of our experiment. We created three heterogeneous customers, varying substantially in the cost of serving (Kaplan and Cooper, 1997).

In Table 1, **revenues** (TR) respond to sales visit hours (x_i) invested in each customer. Appendix A shows that the parameters of the sales response functions (k_i, b_i, λ_i, μ_i, ρ_i) are responsible for important revenue differences between customers (Foster, Gupta and Sjoblom, 1996). Customer A is characterised by a small maximum potential sales volume and maximum sales is achieved by investing a small number of sales visit hours (quick response). Client B has a large potential sales volume but its response to sales visit hours is much slower. Customer C positions itself somewhere in the middle (medium sales volume and medium sales response).

Table 1: The two economic environments and their functional forms (i= A,B,C)

	Concave	**S-shaped**
Total Revenues	$TR_i = k_i [1-\exp(-b_i x_i)]$	$TR_i = \lambda_i + k_i [x_i^{\mu i} / (x_i^{\mu i} + \rho_i)]$
Total Costs		
sales visit cost	$TVC_i = P x_i$	
delivery cost	$TDC_i = (k TR_i)^q + a TR_i$	
logistic cost	$TLC_i = (k TR_i)^q$	
production cost	$TPC_i = m TR_i$	

Cost differences are introduced at the level of three post production costs. The first post production cost in our experiment is **total sales visit cost** (TVC). Subjects have to allocate sales visit hours (x_i), but the cost of using sales visit hours increases as more sales visit hours are allocated to a particular customer. Consistent with marketing assumptions (Foster and Gupta, 1994), we assume that sales visit is a flexible resource. One hour of sales visit is hired at a fixed price P (see Table 1). Other post production costs are **total delivery costs** (TDC) and **total logistic costs** (TLC). In the operations management literature, delivery costs are often assumed to be concave in function of demand (Klincewicz, 1990; Khumawala and Kelly, 1974). By introducing the power $q = ½$ (see Appendix A), both functions become concave in demand, indicating that there are economies to scale in delivering large customers (Klincewicz, 1990). Customer B, characterised by a large demand, will incur proportionally less delivery and logistic costs compared to customer A and C.

Since our focus is on post production costs, **total production cost** (TPC) is defined as a fixed margin of revenue. Figure 1 displays the profit differences in terms of sales visit hours between the three different types of customers for both economic environments.

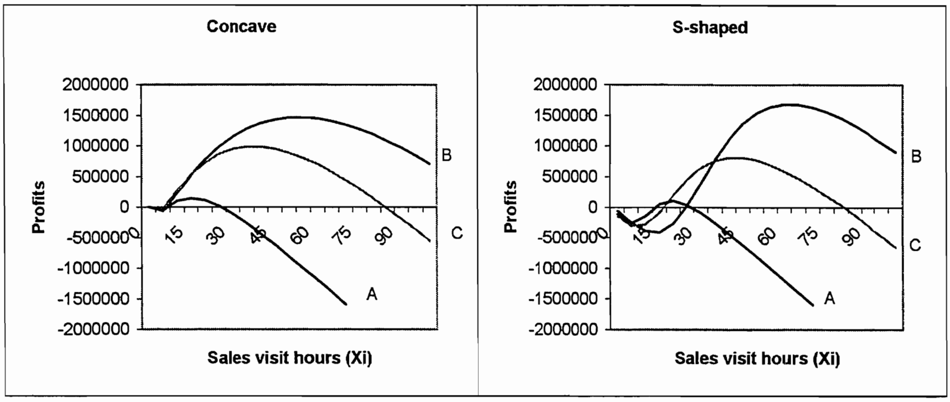

Figure 1: The profit (objective) functions for both economic environments

Manipulation of complexity

There are many factors influencing learning performance in hill climbing problems. Busemeyer, Swenson and Lazarte (1986) define eight factors in which the shape of the objective function is one factor that may influence learning performance. Tversky and Kahneman (1974) define several heuristics that may obstruct learning. One of these heuristics is the anchor and adjustment heuristic. The basic principle is that people given a starting point (initial value) make adjustments from the starting point to yield a final answer. Another starting point will yield a different final answer.

In our experiment we expect learning performance between the two environments to be influenced by the fact that people overallocate (adjustment) the budget of sales visit hours starting from the initial starting point (anchor). Ackoff and Emshoff (1975) describe a case in which marketing managers were unwilling to reduce advertising budgets. Although their research showed that decreasing the budget for advertising could increase profits, managers were unwilling to act on this information.

In our setting subjects started from an allocation policy in which the company initially invested 156 hours in total (52 hours per customer). This can be considered as an anchor point. In both economic environments subjects were 45% away from optimal profit (Appendix B). Figure 2 shows the profits for the large customer in both economic environments, which at the starting point are almost the same. Due to the fact that participants allocate more sales visit hours than the initially installed budget, people in the concave environment are more heavily punished in profits (Figure 2 shows a large decrease in profits) compared to the S-shaped environment (lower decrease in profits). Therefore we define the concave environment as a **complex** learning environment, because subjects must learn that overallocating from the anchor has a more severe impact on profits. The S-shaped environment is more **simple** because the profit consequences of initial overinvestment are much smaller leading subjects to better performance.

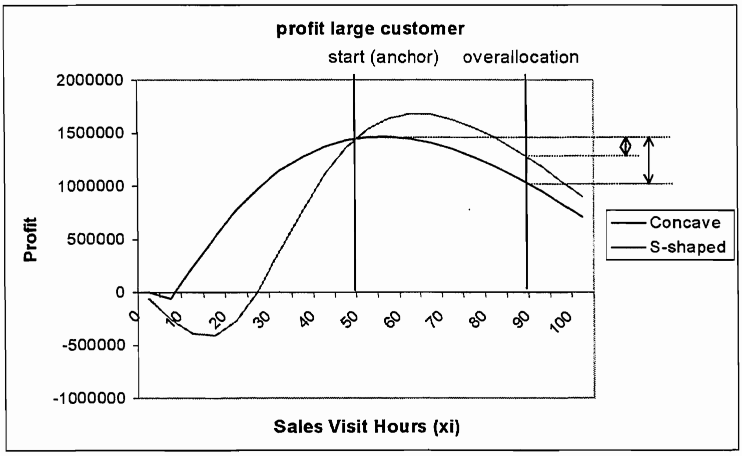

Figure 2: Consequences of overallocation

Given the overinvestment at the starting value, we expect the benefit of CPA over traditional costing system will be more pronounced in the concave (complex) environment than in the S-shaped environment. In other words, CPA information in the complex environment unmasks the severe consequences of overallocation and as a reaction participants will take more appropriate adjustment choices (Busemeyer and Myung, 1987).

Costing systems

The **traditional system** does not display different marketing costs. It is common practice to combine these costs into aggregate functional categories, such as general selling and marketing expenses (Johnson and Kaplan, 1991). In our traditional costing system total customer cost is allocated to individual customers using total revenues as cost driver. This is a poor approximation of reality because high-volume customers will receive costs in function of this large demand, which will overestimate the costs actually incurred. The small customer will be allocated lower costs than actually incurred.

Our **CPA system** has three cost pools, corresponding to real economic cost structure. The three cost pools are total visit costs, logistic costs and delivery costs. For the total visit cost, our CPA system uses total sales visit hours as the activity driver. Hence the allocation of this cost to the three types of customers is the same as real economic cost structure. The activity driver used to allocate the total delivery cost (total logistic cost) to customers is number of deliveries (picking movements). The CPA system assumes that the large customer B needs fewer deliveries (picking movements) compared to the small customer A for the same proportion of demand. It is intuitively clear that in this manner customer B will receive proportionally less delivery costs (logistic costs). This also corresponds with underlying economic cost structure. The concave cost structures created economies of scale in delivering a large customer.

We adhered to three necessary conditions formulated by Noreen (1991) for ABC to provide relevant costs for decision making. The first condition is that total cost can be partitioned into cost pools, each of which depends solely on one activity (cost function being separable). The second condition is that the cost pools have to be strictly proportional to activity. The third condition mentions that the cost driver itself is additive across individual product demands. Noreen and Soderstrom (1994) show that condition two does not always hold in reality, due to economies to scale when the level of activity increases. To make our setting realistic, we define some elements of costs to be concave in demand, representing economies to scale. In the CPA system these costs are approximated by local linear functions. Christensen and Demski (1995) state that if the purpose of the costing exercise is to improve the function of a less than completely specified cost expression, the exercise rests on a cost-benefit test. We design the CPA system in such a way that it approximates the cost consequences of demand heterogeneity and assume that it results into better decision making (benefit of an improved costing system).

Appendix B displays the profit margins in the real economic environment, the CPA-system and the traditional system, at the start of the experiment. It is obvious that CPA information, as accounting feedback, is closer to the real picture. Subjects provided with

CPA, can better judge where they are located on the hill of the objective function for each customer and realise when to reduce or to increase their sales visit hours (Busemeyer, Swenson and Lazarte, 1986). The profit information on customers which subjects receive from traditional systems is less informative because it deviates markedly from economic reality.

4.2. Experimental Task

Participants were recruited from a graduate management accounting course at a large West-European university. They were all graduate students -on average 23 years old- with a university degree, completing a Masters program in applied economics or insurance. The accounting course had already treated the differences between ABC and traditional systems and it had dealt with the use of ABC for customer profitability analysis. A total of 139 students completed the task on a computer. Students were randomly assigned to one of the four experimental conditions when entering the experimental room. Sessions lasted one hour. To induce a motivational aspect, subjects were notified in advance that the four best players would receive a gift coupon[1] for books or CD's worth the counterpart of approximately € 20.

Before the experiment started, students received a few pages of instructions on the computer screen. The subjects were provided with information of a company specialised in the production of home protection systems (electronic shutter systems, fencing systems, fly screens etc...). Participants received a description of the company's three clients that differed in potential sales volume and in the consumption of the company's resources (see cost structure). Client A was described as a self-employed carpenter ordering small quantities in different sizes and colours. Customer B was presented as a building contractor with a large sales volume ordering large quantities of the same sizes and colours. Customer C represented a home protection shop store with a medium size sales volume. Initially the company invested a level of 52 hours per customer, in total 156 sales visit hours (Appendix B). The purpose of the task was to reallocate the budget of sales visit hours, during 10 trials, in order to increase firm profitability. In total subjects could allocate no more than 200 sales visit hours over the three customers.

[1] In reality we rewarded the best player in each of the four conditions with a coupon.

At the starting point, participants in both environments were 45% removed from optimal profit, which gave them ample opportunity to improve. After each trial participants received an imperfect accounting report (see Appendix B) as feedback. Half of the participants were provided with CPA information, while the others received traditional accounting reports. After each trial, the computer displayed the chosen allocation policy and corresponding total profit on the screen, which remained on the screen until the end of the experiment. After completion of the 10 trials, the program automatically finished. Participants filled out a questionnaire, containing several items (on a five-point scale) testing their motivation and their use of accounting information. The 131 students, who filled out the questionnaire correctly, were highly motivated (average: 3.996 and median 4) whereby subjects in the simple environment were slightly more motivated than subjects in the complex condition ($F_{(1, 127)}$: 3.78; $p < .06$). Importantly, no difference in motivation was detected for the accounting report type.

5. Results

This paragraph discusses the main results of the experiment. First of all we report the subject's average score and the subject's best score per experimental cell and draw some preliminary conclusions. The next section introduces a regression model, incorporating the effect that subjects are able to learn over time.

5.1. Summary Statistics

We first of all report the means per experimental cell of the subjects' average percentage opportunity loss over the 10 trials. It is defined as the average of the differences between the optimal profit (π^*) and profits realised by a subject in a round (π_{it}), expressed as a percentage of optimal profit (Gupta & King, 1997):

$$\text{AVG\_LOSS}^2 = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{t} \sum_{j=1}^{t} \frac{\pi^* - \pi_{it}}{\pi^*}$$

n = the number of subjects per cell
t = the number of trials

[2] At the start, the distance from optimal profit in the S-shaped condition was 45,14% whereas in the concave condition this distance was only 44,99 %. We therefore multiply the percentage opportunity loss in the S-shaped condition in each trial with a factor 0,9967 (= 44,99/44,15).

The lower a subject's average opportunity loss, the closer subjects are to optimal profit. We also computed the subject's best score, defined as the round in which the subject is closest to optimal profit. Table 2 reports the result of both test metrics for each experimental condition.

$$BEST = \frac{1}{n}\sum_{i=1}^{n} \operatorname*{Min}_{j=1}^{t}\left[\frac{\pi^{*} - \pi_{it}}{\pi^{*}}\right]$$

n = the number of subjects per cell
t = the number of trials

Table 2: The subjects' average scores and best scores per experimental cell

	Traditional	CPA	$\frac{\pi\,(\text{Trad}) - \pi\,(\text{CPA})}{\pi(\text{Trad})}$
Complex (Concave)			
Mean average % loss	0,36368	0,29538	0,18780
Mean best score	0,18144	0,10151	0,44053
Number of subjects (n)	34	35	
Simple (S-shaped)			
Mean average % loss	0,32199	0,29254	0,09146
Mean best score	0,12465	0,11061	0,11264
Number of subjects (n)	33	37	

Participants receiving CPA do better (lower average opportunity loss and best score) than people provided with traditional accounting systems (H1). People in the S-shaped condition perform better mainly in the case of traditional information, indicating that this is a simpler learning environment. Hypothesis two predicts that the value of a CPA report is higher in a complex (concave) environment. The mean average % loss indicates that the improvement people realise in this environment, by receiving a CPA report **(18,78%)**, is much higher compared to the simple S-shaped condition **(9,146%)**. The difference in value of CPA over traditional info between the two environments is even more pronounced when we look at the subject's best score (see Table 2).

5.2. The regression "learning" model

In this section, we introduce a regression model, which incorporates several learning effects. The model contains main effects of accounting system (to test H1), environment and the interaction of system and environment (to test H2). Besides better accounting information and the influence of the learning environment, decision makers should also be able to learn from mere profit feedback (Gupta and King, 1997). We therefore added cumulative experience (reflected by the trial number) to the model.

The percentage opportunity loss[3] depends thus on the accounting system S (S is 1 for CPA and 0 for Traditional), the environment E (E is 1 for Simple and 0 for Complex), the interaction term SE and on the variable cumulative feedback T (T=1,2,...,10) where T represents the trial number. Besides a linear regression model we also test an inverse relationship between the opportunity loss and the trial number, because we expect a subject's percentage opportunity loss to decline most steeply during the first few trials and gradually decline towards a certain positive value (b_0 in the inverse model). Figure 3 indicates that such a relationship may be present in our data:

Linear Model: $\%L_{i,t} = b_0 + b_1 T + b_2 S + b_3 E + b_4 SE + e$

Inverse Model: $\%L_{i,t} = b_0 + b_1 \frac{1}{T} + b_2 S + b_3 E + b_4 SE + e$

Where $\%L_{i,t}$ is the percentage deviation against optimal profit for subject i (i = 1,2,...,139) in trial t (t = 1, 2,..., 10). This gives in total 1390 observations;

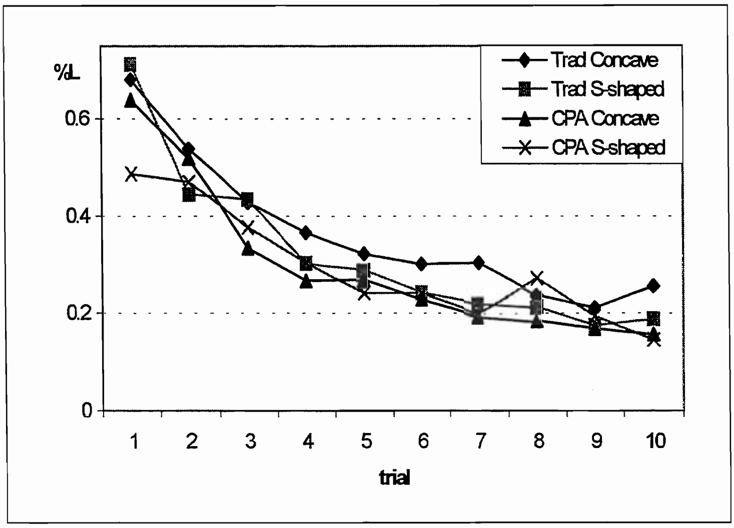

Figure 3: Trial by trial average opportunity loss (%L) in the four experimental conditions

[3] defined as the subject's percentual distance from optimal profit in round t: $\%L_{i,t}=(\pi^* - \pi_{i,t})/\pi^*$

Inherent in learning tasks is the presence of non-constant variance of the error terms (heteroscedasticity). Because of the fact that participants gain experience in the task (T), we expect the variance of the error terms to decrease over the trials. White's (1980) general test for heteroscedasticity concluded that the error terms in both our models lacked constant variance. The weighted least squares method[4] which corrects for non-constant variance of the error terms (Neter, Kutner, Nachtsheim and Wasserman, 1996) was used to estimate the coefficients. These regression results are given in Table 3; White's test indicated no presence of heteroscedasticity.

Table 3: Results of the regression analysis for both models using weighted least squares (n=1390)

	Parameter estimates	
	LINEAR	**INVERSE**
Intercept	0.5618 *	0.2027 *
Cumul (T)	-0.0375 *	0.5414 *
System (S)	-0.0714 *	-0.0714 *
Environ (E)	-0.0460 **	-0.0460 **
Syst*Envir (SE)	0.0549 **	0.0549 **
F-value	59.184 *	67.238 *
Adjusted R^2	0.1435	0.1602

* Significant at the 1% level
** Significant at the 5% level

The variable T is significant at the 1% level. Although provided with imperfect cost reports, people improve over time, indicating that they are able to learn from total profit feedback. The inverse model has a higher R-square indicating that improvements are sharp during the first rounds and gradually decline to a certain positive value. The inverse model assumes that the learning ability of a decision maker is limited because after a certain number of trials he will not improve anymore.

Hypothesis H1 is confirmed at the 1% significance level. People receiving customer profitability information perform better (lower opportunity loss) than subjects receiving traditional accounting systems in both environments. A CPA report apparently provides more relevant information for subjects applying hill climbing heuristics. Items in the post questionnaire checked the subject's use of accounting information for both accounting systems. They revealed that participants in the traditional condition used the

[4] We used square root of T as weight, assuming that the variance of the error terms decreased with T.

cost reports less extensively to ($F_{(1, 127)}$: 3.96; $p < .05$) and that they considered the cost reports to be less relevant ($F_{(1, 127)}$: 5.86; $p < .02$). People receiving CPA concentrated more on profit margins per customer compared to participants receiving traditional accounting systems ($F_{(1, 127)}$: 11,74; $p < .01$), reinforcing the conclusion that CPA provided more relevant information for the decision.

The interaction term has the correct sign and is significant at the 5% level, thereby confirming hypothesis H2. A CPA report has more value in a complex learning environment compared to the more simple S-shaped condition. These results largely depend on the fact that subjects tend to overallocate the budget of sales visit hours. Appendix C shows that overallocation manifests itself during every trial. However, subjects in the CPA condition did start closer to optimal allocations (especially for the least profitable customer C) and learned better from experience (more appropriate allocation choices for customer A and B in later trials). The incremental value of a CPA system in a complex environment is due to the fact that CPA illuminates the severe consequences of overallocation. Subjects in a complex environment receiving CPA therefore reduced the budget with larger amounts (see appendix C; reduction of 55 hours), tempering the consequences of overallocation. From these results it is clear that CPA subjects in the complex condition do better because the accounting system provides them with the opportunity to alleviate the anchoring bias (Tversky and Kahneman, 1974) caused by the starting allocations.

6. Discussion

Our experiment demonstrated that decision makers receiving customer profitability analysis (CPA) reports were able to make more profitable marketing budget allocation decisions compared to decision makers receiving traditional accounting information. In contrast to prior research (Gupta and King, 1997), we also found that the benefit of CPA was more pronounced in a more complex learning environment. We attribute this difference to our choice for a complex learning situation, which more closely reflects the learning difficulties faced in real business decision environments. Real world cost and demand functions are rarely, if ever, linear. Prior research may have been operating at the low end of environmental complexity, in which the added value of good accounting information is hard to detect.

In our study, part of the complexity was also induced by making the participants start from an initial overall budget that was higher than optimal. Marketing decision makers may be overly reluctant to decrease budgets due to the general belief that one needs to increase budgets in order to increase sales. If profits would decline after a budget decrease, it would be easy for the company to attribute the failure to the manager's action. A profit decrease following a budget increase is more readily attributed to unforeseen external circumstances. Other priors may influence allocation decisions as well. For example, decision makers may be inclined to allocate budgets proportional to sales volume, or use other situation and case-specific decision rules. Obviously, such decision rules – in reality just like in our experiment – are not always warranted by the data.

Decision makers improve their budget allocations period by period, based on the accumulating outcome feedback and using additional costing information they receive. Priors and biases may slow down this learning process. In general, the benefit of accounting information in managerial decision making is that it allows the manager to make data driven decisions, rather than having to rely on possibly faulty priors. Costing systems facilitate learning to the extent that they provide the manager with specific data allowing the manager to diagnose the invalidity of her priors and decision heuristics. In our study, customer level cost information on a highly heterogeneous set of customers provided the decision makers with these specific data.

Obviously the manager also learns from mere outcome feedback. Even without costing information, adaptations in successive allocations are not random. The manager learns from prior successes and mistakes. The heuristic guiding this learning process has previously been described as hill climbing. We argue that additional accounting information will help the decision maker to fine-tune the hill climbing process. Its largest benefit should come when a decision results in a decrease of profits compared to prior periods. Hill climbing then prescribes a change of policy, but in most cases many alternatives for change are open to the decision maker. Good accounting information proves its value because it will help reduce the set of alternative courses of action to those that have a higher probability of being successful.

One may wonder whether traditional accounting information with sales-based cost allocations provides *any* information over mere outcome feedback to improve the hill climbing process. Decision makers may even stop paying attention to this information when they learn that it does not help them improve allocation decisions. To the extent that they do continue to pay attention, a traditional system may promote the use of unwarranted decision rules (like allocating proportional to sales). Future research may concentrate on the nature of the learning process through which hill climbing becomes more efficient. It could examine which level of task specificity of the information is needed to help decision makers alleviate existing (or experimentally induced) biases.

In the current study we manipulated complexity on the demand side. This is justifiable in a marketing scenario, but there are of course many different sources of complexity. Prior research studying production allocation decisions introduced heterogeneity and complexity on the cost side. Cost and demand side complexities may be studied in more detail in future research.

In our study, the CPA condition differed from the traditional information condition not only in the specificity and appropriateness of the information but also in the mere amount of information. Future work should try to disentangle these two effects. Decision makers may be more motivated when the mere volume of information is higher. Motivation may also increase because the decision maker learns that the information helps her to control the situation and maker better decisions. But merely increasing the amount of information may have adverse consequences when the additional information is not diagnostic for the specific task under study. This information may misguide the decision maker.

There has now been a relatively long history of discussion about the benefits of CPA, and other ABC systems, relative to traditional costing systems. Further progress requires a change of focus from *whether* ABC systems have beneficial effects to *when* and especially *how* and *why* these effects are obtained. Only detailed descriptive research into the role accounting information plays in the processes of making decisions and learning to make better decisions will allow us to build adequate theory, which in turn can guide pragmatic advice to the business community.

APPENDIX A

Values of parameters for the revenue functions

	CONCAVE		S-SHAPED			
	k	b	λ	k	μ	ρ
TR_A (small)	5000000	0,0900	750000	4250000	3,00	2000
TR_B (large)	15000000	0,0254	1000000	14000000	2,90	34200
TR_C (medium)	11000000	0,0380	500000	10500000	2,19	1200

Values of the parameters for the cost functions

TVC	P=40000
TDC	k=110000; a= 0.01; q =½
TLC	k=50000; q=½
TPC	m=0.50

APPENDIX B

The company initially invested 52 sales visit hours in every customer. In the case of concave sales response functions, this results in a deviation of about 45% from optimal profit so there was opportunity to improve. The S-shaped function also deviates 45% from optimal profit but is not displayed here. The real underlying cost structure (beneath; concave environment) shows that customer A is generating a loss. Subjects do not receive this kind of information; they receive imperfect cost reports after every trial.

Real economic environment (concave response functions)

	CUST A	margin	CUST B	margin	CUST C	margin	TOTAL	margin
Xi	52		52		52		156	
TR	4953605		10996175		9475151		25424931	
TPC	2476802	50.00%	5468087	50.00%	4737576	50.00%	12712465	50.00%
TCC	3365382	67.94%	4031261	36.66%	3883967	40.99%	11280610	44.37%
TVC	*2080000*	*41.99%*	*2080000*	*18.92%*	*2080000*	*21.95%*	*6240000*	*24.54%*
TDC	*787707*	*15.90%*	*1209770*	*11.00%*	*1115666*	*11.77%*	*3113144*	*12.24%*
TLC	*497674*	*10.05%*	*741491*	*6.74%*	*688301*	*7.26%*	*1927466*	*7.58%*
π	-888580	**-17.94%**	1466826	**13.34%**	853609	**9.01%**	1431856	5.63%

Optimal π	% deviation
2602705	44.99%

At the start of the experiment, subjects in the CPA condition received following customer profitability report as feedback. Clearly, the information is very close to reality. Customer A is generating a loss in reality, which is also indicated in a CPA report.

Profitability report on the basis of customer profitability information (CPA)

	CUST A	margin	CUST B	Margin	CUST C	margin	Total	margin
Revenue	4953605		10996175		9475151		25424931	
Production cost	2476802	50.00%	5498087	50.00%	4737576	50.00%	12712465	50.00%
Customer cost	3491972	70.50%	3812906	34.67%	3975733	41.96%	11280610	44.37%
Driver rate	#	*cost*	#	*Cost*	#	*cost*		
visit 40000	52	2080000	52	2080000	52	2080000		
delivery 4111	198	814537	275	1130085	284	1168522		
logistics 1096,4	545	597435	550	602820	663	727211		
Profit	-1015169	**-20.5%**	1685182	**15.33%**	761843	**8.04%**	1431856	5.63%

Participants in the traditional scenario only received following information at the start. They merely can rely on total cost figures. The profit margin is for each customer the same and customer A is even indicated as profitable.

Profitability report on the basis of traditional information

	CUST A	margin	CUST B	Margin	CUST C	margin	Total	margin
Revenue	4953605		10996175		9475151		25424931	
Production cost	2476802	50.00%	5498087	50.00%	4737576	50.00%	12712465	50.00%
Customer cost	2197830	44.37%	4878816	44.37%	4203964	44.37%	11280610	44.37%
Profit	278972	**5.63%**	619272	**5.63%**	533612	**5.63%**	1431856	5.63%

It is useful to get an insight on how total delivery costs (**3.133.144**) are allocated using a CPA system with number of deliveries as an activity driver compared to a traditional system using total revenues as cost driver. The CPA assumes that customer B needs in proportion to its demand, fewer deliveries compared to customer C and A.

	# deliveries per 100000 revenues	**Revenues (TR)**
A (small)	4	4953605
B (large)	2,5	10996175
C (medium)	3	9475151
	Total revenue	25424931

Number of deliveries for customer A = $\frac{4 \text{ x } 4953605}{100000}$ = 198,1442 deliveries

Number of deliveries for customer B = $\frac{2.5 \text{ x } 10996175}{100000}$ = 274,9044 deliveries

Number of deliveries for customer C = $\frac{3 \text{ x } 9475151}{100000}$ = 284,2545 deliveries

Total number of deliveries = 757,3031 deliveries

Cost driver rate = $\frac{3113144}{757,3031}$ = 4110,8296 cost per delivery

Delivery cost allocated to A = 4110,8296 x 198,1442 = 814537 (16,44%)
Delivery cost allocated to B = 4110,8296 x 274,9044 = 1130085 (10,27%)
Delivery cost allocated to C = 4110,8296 x 284,2545 = 1168522 (12,33%)

In a **traditional costing** system, total revenue is used to allocate delivery costs (which can be easily computed). The table beneath displays that allocations generated by a CPA system are closer to real economic cost structure compared to the traditional systems. The same exercise can be done for the logistic costs and will give similar conclusions.

	TDC (Real)	Margin	TDC (CPA)	Margin	TDC (Trad)	Margin
Customer A	787707	15,90%	814537	16,44%	606542	12,24 %
Customer B	1209770	11,00%	1130085	10,27%	1346421	12,24 %
Customer C	1115666	11,77%	1168522	12,33%	1160181	12,24 %
Total	3113144	12,24%	3113144	12,24%	3113144	12,24%

APPENDIX C

AVERAGE ALLOCATION PER TRIAL AND PER EXPERIMENTAL CONDITION

TRAD_CONCAVE

	A	B	C	TOT
T1	40.2	81.8	55.2	177.2
T2	46.0	62.7	51.6	160.3
T3	35.5	65.8	51.4	152.7
T4	31.3	62.5	52.3	146.1
T5	27.5	63.3	50.3	141.1
T6	27.5	64.3	45.0	136.8
T7	27.9	63.0	48.3	139.3
T8	26.5	61.2	42.7	130.5
T9	24.9	62.0	42.1	129.0
T10	25.3	65.9	41.4	132.5
opt	***15.0***	***53.0***	***37.0***	***105.0***

Difference in total hours allocated between the first and the last trial ***44.7***

TRAD_S-SHAPED

	A	B	C	TOT
T1	47.8	79.1	57.7	184.6
T2	41.1	78.9	54.8	174.7
T3	37.9	77.2	53.5	168.6
T4	34.0	74.5	50.5	159.0
T5	30.6	72.4	50.8	153.8
T6	29.6	67.5	50.3	147.4
T7	26.6	69.3	50.5	146.4
T8	25.3	70.2	49.5	145.0
T9	24.5	67.6	47.7	139.9
T10	25.4	67.6	47.7	140.7
opt	***19.0***	***62.0***	***42.0***	***123.0***

Difference in total hours allocated between the first and the last trial ***43.9***

CPA_CONCAVE

	A	B	C	TOT
T1	39.9	82.8	56.2	178.9
T2	34.1	70.3	58.6	163.1
T3	25.2	68.5	51.8	145.5
T4	23.2	66.7	49.2	139.1
T5	18.6	58.3	45.7	122.6
T6	19.7	60.3	49.1	129.2
T7	15.2	61.8	49.4	126.4
T8	17.3	59.1	46.2	122.6
T9	16.3	62.2	44.2	122.7
T10	16.1	61.8	45.1	123.0
opt	***15.0***	***53.0***	***37.0***	***105.0***

Difference in total hours allocated between the first and the last trial ***55.9***

CPA_S-SHAPED

	A	B	C	TOT
T1	**36.4**	**77.7**	**62.5**	**176.6**
T2	33.7	74.5	57.2	165.4
T3	28.2	68.8	53.6	150.6
T4	24.6	69.8	54.6	149.0
T5	20.4	69.3	51.1	140.8
T6	18.0	71.1	49.3	138.4
T7	16.7	71.7	49.9	138.3
T8	19.0	65.3	47.7	132.0
T9	17.1	66.2	47.0	130.3
T10	16.3	68.1	48.7	133.1
opt	***19.0***	***62.0***	***42.0***	***123.0***

Difference in total hours allocated between the first and the last trial ***43.5***

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